Online Appendix to "Media Capture through Favor Exchange"*

Adam Szeidl
Central European University and CEPR

Ferenc Szucs
Stockholm University

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A1 Cross-country evidence on media favoritism

We review suggestive evidence on two-way favors in a number of democracies. We classify a country as experiencing media favoritism if at least one source discusses anecdotal, informal or correlational evidence on substantial advertising favors in the present or recent past. And we say that government advertising is an important source of revenue in the media market of the country if the source say so.

Our sources are a report by the European Parliament's Policy Department on Citizen Rights and Constitutional Affairs, Bard and Bayer (2016) (EP report); a report by the Open Society Foundation on Mapping Digital Media, Dragomir and Thompson, eds (2014), which summarizes findings from many country reports on the status of digital and conventional media (MDM); several Freedom House reports on freedom of the press in different countries; academic and policy papers; newspaper articles; and blog posts. The EP report is a careful investigation of media freedom in a number of EU countries and is our main source for the EU. In MDM, Table 12 provides information, for many countries, on: whether the government supports media financially, the type of support (e.g., government advertising), whether such funding is used to manipulate media, and whether state funding is significant. For each country we identify below, we checked both the MDM summary report and the associated individual country report. Some countries MDM classifies as experiencing media favoritism are not included in our selection: e.g., we did not include Spain because the favors MDM highlight are ideology based, such as advertising in Catalan newspapers by the Catalan government. And we did include some countries MDM did not classify as experiencing media favoritism if more recent evidence shows such favoritism.

Table A1 shows the resulting list of countries and the specific sources of evidence. For the vast majority of these countries the same sources also claim that government advertising is an important source of revenue for the media, with the exceptions of Slovakia and Slovenia for which we did not find any evidence on the importance of government advertising. Based on this list we estimate

*Emails: szeidla@ceu.edu, ferenc.szucs@ne.su.se.

Table A1: Suggestive evidence on two-way favors between the government and the media

Country	Source of evidence
European Union	
Bulgaria	MDM, EP report
Greece	EP report
Hungary	MDM, EP report
Poland	EP report
Romania	MDM, EP report
Slovakia	Transparency International Slovensko (2013)
Slovenia	MDM, Freedom House (2015c)
Rest of Europe	
Albania	MDM, Freedom House (2015a)
Macedonia	MDM, Trpevska and Micevski (2015)
Serbia	MDM, Freedom House (2015b)
Turkey	Yanatma (2016)
Americas	
Argentina	MDM, DiTella and Franceschelli (2011)
Brazil	Nunes (2016)
Colombia	MDM, Hart (2019)
Mexico	MDM, Ahmed (2017)
Asia	
India	MDM, Ghoshal (2019)
Pakistan	MDM, Ellis-Petersen and Baloch (2019)

that over 18% of citizens in the EU, and over 2 billion people worldwide, live in democracies that experience media favoritism.

Ownership changes. Evidence suggests that declining private advertising in the print media was accompanied by the takeover of multinational-owned outlets by domestic owners with government ties in both the Czech Republic (Cisarova and Metykova 2015, Rybkova and Rihackova 2013) and Hungary (MMM 2017). In the Czech Republic, leading media group Mafra was sold by Rheinisch-Bergische Verlagsgesellschaft to the politician Andrej Babiš in 2013. In Hungary, besides Telekom selling Origo, Ringier and Axel Springer also sold their ownership in several newspapers, including a number of regional dailies, which eventually ended up owned by a company linked to a personal friend of the prime minister (MMM 2017).

A2 Regression evidence on two-way favors

A2.1 Favors from the government to connected media

Left- versus right-connected daily. We aggregate the spending of each advertiser in each of the two main dailies to the the electoral cycle level, and estimate

$$\text{Right share}_{ac} = \text{const} + \sum_{l=1}^{m} \rho_l \cdot \text{advertiser category}^l_{ac} \times \text{right cycle}_{ac} + \text{controls} + \mu_c + \varepsilon_{ac}. \quad \text{(A1)}$$

The dependent variable is "Right/(Left+Right)", the share of advertising in the right-connected daily relative to advertising in the two dailies, measured at the level of an advertiser a in a given electoral cycle c. Advertiser categories can be private firms, state-owned firms, and different types of government agencies; and the controls include either indicators for advertising categories or—in more demanding specifications—advertiser fixed effects. We always include cycle fixed effects μ_c. We drop (a, c) observations when a enters the advertising data in the last half year, or exists the data in the first half year of cycle c. Our main interest is in the ρ_l coefficients, which measure, by advertiser category, the extent to which the composition of advertising differs when the right is in power.

Table A2 reports the results. We focus on four advertiser categories: (i) state-owned firms; (ii) government agencies involved in administration, such as ministries; (iii) government agencies involved in public goods provision, such as hospitals or theatres; and (iv) private firms, which are the omitted category. Columns 1 and 2 present unweighted specifications which measure the behavior of the average advertiser. Column 1 is a baseline specification without advertiser fixed effects. Relative to the omitted category of private firms, state-owned firms changed the composition of advertising substantially more with the political cycle: they allocated 26 percentage points more of their advertising budget to the right-connected newspaper under right-wing governments than under left-wing governments. Administrative government agencies allocated 25 percentage points more, and public good providing agencies allocated 12 percentage points more to the right-connected newspaper under right-wing governments. All these estimates are highly significant. In column 2 we include advertiser fixed effects. These soak up level differences between government-controlled and private advertisers, and identify the effect of changes in government from time-series variation *within* advertisers. The results are essentially unchanged.

Columns 3 and 4 repeat these specifications but—following DellaVigna, Durante, Knight and La Ferrara (2015)—weight observations by the total value (at list prices) of the advertiser's advertising in the two newspapers. With these weights, the results measure how the allocation of the average advertising dollar changed with the political cycle. For state-owned firms and administrative government agencies the patterns are similar to columns 1 and 2, but the magnitudes are larger. Intuitively, large advertisers shifted their spending more than small advertisers. For example, column 4 shows that the share of state-owned firms' advertising allocated to the right-connected daily increased by 34 percentage points under right-wing governments. A possible explanation—which also

Table A2: Daily newspapers: political cycle and advertising composition

Dependent variable:	Share of right-connected daily, R/(L+R)			
	unweighted		weighted	
State-owned × right cycle	0.260***	0.240***	0.379***	0.343***
	(0.0298)	(0.0283)	(0.0536)	(0.0589)
Govt. agency (admin) × right cycle	0.248***	0.201***	0.459***	0.435***
	(0.0367)	(0.0404)	(0.0581)	(0.0634)
Govt. agency (public good) × right cycle	0.119***	0.128***	0.0702**	0.0823***
	(0.0332)	(0.0322)	(0.0307)	(0.0279)
State-owned	0.0942***		0.126***	
	(0.0203)		(0.0286)	
Govt. agency (admin)	0.146***		0.0415	
	(0.0258)		(0.0302)	
Govt. agency (public good)	0.133***		0.0832	
	(0.0252)		(0.0661)	
Advertiser FE		X		X
Cycle FE	X	X	X	X
Observations	3053	3053	3053	3053

Note: Each observation is an advertiser × cycle pair. The sample contains the top 500 private, all state-owned, and all government agency advertisers for 1994-2014. Columns 3 and 4 are weighted by total advertising in the two newspapers. Standard errors clustered by advertiser in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

helps explain the smaller reallocation of public-good providing agencies—is that larger advertisers were under tighter political control.

Metropol. Because for Metropol we are interested in the immediate effect of the change in ownership, we conduct an event study. Focusing on the sample of private firm and state-owned firm advertisers, zooming in on the two-year window surrounding the acquisition, and using quarterly data, we estimate

$$\text{Metropol share}_{at} = \text{const} + \sum_{-4 \leq q \leq 3, q \neq -1} \rho_k \cdot \text{state owned}_{at} \times \text{post acquisition}_t^q + \text{controls} + \varepsilon_{at}. \quad \text{(A2)}$$

The dependent variable is measured as "Metropol/All", that is, the share of the advertising spending of advertiser a in quarter t in the print market which is allocated to Metropol. And *post acquisition*$_{it}^{q}$ is an indicator for the q-th quarter after Metropol was acquired by the right-connected business group, where a negative q denotes a period before the acquisition. We omit the period immediately before the acquisition ($q = -1$), hence we compare changes in the public-to-

Table A3: Metropol: ownership change and advertising composition

Dependent variable:	Share of Metropol, Metropol/All			
	unweighted		weighted	
State-owned × pre-acquisition 4	0.0251	-0.0167	-0.00142	0.000392
	(0.0495)	(0.0484)	(0.0855)	(0.0857)
State-owned × pre-acquisition 3	-0.000873	-0.00425	-0.00910	-0.00163
	(0.0332)	(0.0291)	(0.0255)	(0.0219)
State-owned × pre-acquisition 2	0.0102	-0.00869	0.000276	-0.00665
	(0.0400)	(0.0365)	(0.0425)	(0.0424)
State-owned × post-acquisition 0	0.0709	0.0409	0.284^{***}	0.290^{***}
	(0.0463)	(0.0413)	(0.106)	(0.106)
State-owned × post-acquisition 1	0.0659	0.0455	0.239^{***}	0.248^{***}
	(0.0451)	(0.0433)	(0.0875)	(0.0868)
State-owned × post-acquisition 2	0.0991^{*}	0.100^{*}	0.312^{***}	0.317^{***}
	(0.0536)	(0.0540)	(0.0681)	(0.0594)
State-owned × post-acquisition 3	0.106^{*}	0.0805	0.316^{***}	0.312^{***}
	(0.0608)	(0.0608)	(0.0687)	(0.0682)
Advertiser FE		X		X
Quarter FE	X	X	X	X
Observations	2876	2876	2876	2876

Note: Each observation is an advertiser × quarter pair. The sample contains the top 500 private and all state-owned advertisers in a 2 year window around the acquisition in 2011. Columns 3 and 4 are weighted by total advertising in daily newspapers. Standard errors clustered by advertiser in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

private advertising gap relative to this quarter. As controls we always include quarter effects, and either an indicator for state-owned firms or advertiser fixed effects.

Table A3 shows the results. Confirming the graphical evidence, state-owned firms shifted advertising to Metropol right after the acquisition. Columns 1 and 2 show that the average state-owned firm increased the share of advertising allocated to Metropol by a marginally significant 10 percentage points by the second quarter after the acquisition. The weighted specifications show more rapid, larger, and more significant adjustment: for example, in column 4 we see an immediate and persistent effect of well over 20 percentage points ($p < 0.01$ in all quarters). Larger advertisers responded faster and tilted more.

Online media. For online media we focus on the sample of private firm, state-owned firm and

Table A4: Origo: connection changes and advertising composition

Dependent variable:	Share of Origo, O/(I+O)			
	unweighted		weighted	
State-owned × new editor	0.193**	0.210***	0.218***	0.182**
	(0.0827)	(0.0733)	(0.0625)	(0.0721)
State-owned × new owner	0.568***	0.567***	0.607***	0.590***
	(0.144)	(0.176)	(0.186)	(0.198)
Govt. agency (admin) × new editor	0.428***	0.438***	0.276**	0.322***
	(0.0823)	(0.0873)	(0.112)	(0.0908)
Govt. agency (admin) × new owner	0.448***	0.517***	0.383	0.395
	(0.140)	(0.149)	(0.304)	(0.300)
Govt. agency (public good) × new editor	-0.0314	-0.0524	-0.0518	-0.0364
	(0.0731)	(0.0741)	(0.0987)	(0.104)
Govt. agency (public good) × new owner	-0.0832	-0.103	-0.167	-0.174
	(0.0931)	(0.130)	(0.208)	(0.229)
State-owned	-0.204**		-0.293***	
	(0.0926)		(0.108)	
Govt. agency (admin)	-0.298***		-0.171**	
	(0.0625)		(0.0677)	
Govt. agency (public good)	-0.109		0.0454	
	(0.0711)		(0.123)	
Advertiser FE		X		X
Quarter FE	X	X	X	X
Observations	3846	3846	3846	3846

Note: Each observation is an advertiser × quarter pair. The sample contains the top 500 private, all state-owned, and all government agency advertisers in 2013-2016. Columns 3 and 4 are weighted by total advertising in the two portals. Standard errors clustered by advertiser in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

government agency advertisers, consider the period 2013-16 and estimate using quarterly data

$$\begin{aligned}\text{Origo share}_{at} = \text{const} &+ \sum_{l=1}^{m} \rho_l^e \cdot \text{advertiser category}_{at} \times \text{new editor}_t \\ &+ \sum_{l=1}^{m} \rho_l^o \cdot \text{advertiser category}_{at} \times \text{new owner}_t + \text{controls} + \varepsilon_{at}. \quad \text{(A3)}\end{aligned}$$

Table A5: Corruption coverage in dailies around fallout

Dependent variable:	Share of articles on corruption (pp)	
	All three dailies	Right and left daily
Affected right-wing daily × post fallout	1.265***	0.735***
	(0.230)	(0.246)
Left-wing daily × post fallout	0.0596	
	(0.282)	
Affected right-wing daily	-0.258	-1.712***
	(0.157)	(0.178)
Left-wing daily	1.924***	
	(0.221)	
Month FE	X	X
Observations	84	92

Note: Each observation is a newspaper × month pair. Dependent variable measured in percentage points. Column 1 uses all three dailies for 2014.7 - 2016.10. Column 2 uses the two main dailies for 2013.1-2016.10. Heteroscedasticity corrected standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The dependent variable is measured as "Origo/(Index+Origo)", that is, the share of the advertising spending of advertiser a in quarter t in the combined market of the two main portals which is allocated to Origo. And $\textit{new editor}_t$ respectively $\textit{new owner}_t$ are indicators for the period when Origo had a new editor during the Telekom ownership, and the period when Origo had a new owner connected to the governor of the central bank. As controls we always include quarter effects, and either an indicator for state-owned firms or advertiser fixed effects.

Table A4 shows the results. Compared to the period before the events, state-owned firms increased their advertising share on Origo (relative to private firms) by 18-22 percentage points after the change in editor, and by 57-61 percentage points after the change in owner. Both effects are significant in all specifications. The results are slightly weaker but broadly similar for administrative agencies, and are insignificant and small for public good providing agencies.

A2.2 Favors from connected media to the government

Print media. To infer the statistical significance of the observed shift in coverage, we estimate

$$\text{Corruption coverage}_{it} = \text{const} + \sum_{i=1}^{n} \eta_i \cdot \text{newspaper}_i \times \text{post fallout}_t + \iota_i + \mu_t + \varepsilon_{it}. \tag{A4}$$

Observations are newspaper × month pairs, and the dependent variable is the share of articles in newspaper i in month t which cover corruption scandals. The controls always include newspaper and month fixed effects. The η_i coefficients of the interactions measure the change in coverage in newspaper i after the fallout.

Table A6: Corruption coverage in online portals

Dependent variable:	Share of articles on corruption (pp)	
Origo × new editor	-0.442*	-0.442***
	(0.262)	(0.105)
Origo × new owner	-1.358***	-1.358***
	(0.296)	(0.212)
Origo	-0.111	-0.111
	(0.187)	(0.0848)
Period FE	X	
Month FE		X
Observations	92	92

Note: Each observation is a portal × month pair. Dependent variable measured in percentage points. Sample is two main online portals in 2013.1-2016.10. Heteroscedasticity corrected standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5 reports the results. Column 1 shows a specification for the period 2014 July - 2016 October, during which we have content data for all three newspapers. The uninteracted coefficients compare corruption coverage across newspapers before the fallout. These reveal that relative to the unaffected right-connected daily (the omitted category), the left-connected daily covered corruption in a significantly higher share of articles (1.9pp), while the affected right-connected daily covered corruption in a slightly lower share of articles (-0.3pp).

The interactions show that corruption coverage did not change after the fallout in the left-connected daily Népszabadság, but did significantly increase in the affected right-connected daily Magyar Nemzet (1.3 pp). Column 2 shows a specification that includes only the two main political newspapers, the affected right-connected daily and the left-connected daily. Because for these two papers online content was available for a longer time window, this specification goes back to 2013 January. The patterns are similar. The significant gap between these dailies' corruption coverage before the fallout (1.7pp) fell significantly (by 0.7pp) after the fallout.

Online media. To assess significance of coverage changes in online media, we estimate a variant of (A4) for Origo and Index. Table A6 reports the results. Compared to the period before the events, corruption coverage on Origo (relative to Index) declined by 0.4 percentage points after the change in editor, and by 1.4 percentage points after the change in owner. Both of these changes are significant.

Table A7: Key demographics of Index and Origo readers

	Budapest	County capital	Other city	Village	High skill	High status
Origo × new editor	-0.00167	0.00449	0.000570	-0.00469	-0.0189	-0.0166
	(0.0202)	(0.0252)	(0.0175)	(0.0133)	(0.0165)	(0.0337)
Origo × new owner	0.00296	-0.00864	-0.000768	0.00670	-0.00111	0.00119
	(0.0104)	(0.0118)	(0.0140)	(0.0122)	(0.0158)	(0.0276)
Origo	-0.0878***	0.0159	0.0356**	0.0360***	-0.0763***	-0.0661**
	(0.00893)	(0.00980)	(0.0110)	(0.00787)	(0.0124)	(0.0271)
Month FE	X	X	X	X	X	X
Observations	21	21	21	21	21	21

Note: Each observation is an outlet × month pair. Sample contains May and September for 2013, March and September for 2014-17, and February for 2018. Observations weighted by the total number of real users in the given cell. Heteroscedasticity corrected standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A3 Additional reduced form evidence

A3.1 Evidence on audiences

Demographics of online news consumers. We obtained data from a media company on the demographics of the readers of Origo and Index, for two months in each year during 2013-17 and for one month in 2018. Unfortunately analogous data for the print market are not available. Using these data at the (outlet,month) level, we estimate

$$\text{Reader demographics}_{it} = \text{const} + \kappa^e \cdot \text{Origo}_i \times \text{new editor}_t + \kappa^o \cdot \text{Origo}_i \times \text{new owner}_t + \iota \cdot \text{Origo}_i + \mu_t + \varepsilon_{it}, \tag{A5}$$

weighting observations by the total number of readers in the given (outlet,month) cell. Table A7 presents the results for six demographics: the share of readers from Budapest, county capitals, other cities, and villages; and the share of high skilled and high social status readers. Origo was initially slightly less urban, educated and rich. But the interaction coefficients are all insignificant and small: the initial differences persisted after the change in editor and the change in owner. We conclude that the audiences of Origo and Index evolved in parallel, and thus audience demographics are unlikely to have driven the changes in advertising or content.

Political preference of pre-existing readers. Ideally we would like to track not just the demographics but also the political preferences of outlets' readers over time. Although such data are not available in a panel, we do have data from a representative survey in 2013 with 4043 respondents on political preferences, demographics and media consumption. We use these data for two purposes. (i) We compare the readers of Origo and Index, and of Magyar Nemzet and Népszabadság, in 2013. (ii) Exploiting repeated cross-sections of political opinion polls during 2013-17 (which do not include media consumption), we compare the evolution of political preferences of the demographics reading the various outlets.

In 2013, in the online market, the share of readers supporting the government party was 24 percent for both Origo and Index. The share of readers supporting the left-wing opposition was 15 percent in Origo and 17 percent in Index (p-value of equality 0.139). This similarity is unsurprising since the overlap between the readers of Origo and Index was 69 percent. In the print market, among the readers of Magyar Nemzet 44 percent, among the readers of Népszabadság 18 percent supported the government party, while 18 percent respectively 44 percent supported the left-wing opposition. These differences are not surprising since the overlap in readers was only 17 percent.

We explore the dynamics of pre-existing readers' political preferences in two steps. First, we estimate a propensity score of being the reader of a given outlet in 2013 using schooling attainment, settlement type, county, age and age squared as explanatory variables. Second, we use these propensity scores to reweight (respondent, outlet) observations from opinion polls during 2013-17.[1] Using the reweighted data we estimate regressions similar to (A5) with reader political preference for the government party as the dependent variable. We draw inference by bootstrapping the two stage procedure.

The credibility of this procedure is supported by the fact that in the 2013 data our demographics predict well the political preferences of the readers of Origo, Index and Magyar Nemzet. Unfortunately they do not predict well for left-leaning daily Népszabadság: intuitively, readers of Népszabadság are relatively old and rural, which on average predicts a preference for the right. Because of this issue, we compare the evolution of the predicted readers of Magyar Nemzet not just with the predicted readers of Népszabadság but also with those of Index.

Table A8 reports the results (in percentage points). Column 1 compares the predicted readers of Origo and Index, column 2 those of Magyar Nemzet and Népszabadság, and column 3 those of Magyar Nemzet and Index. Initially, predicted Origo readers were less likely to support the government party than predicted Index readers. This gap remained unchanged after the change in editor; and if anything predicted Origo readers became slightly less pro-government after the change in owner. For Magyar Nemzet the estimates are less precise because there were only 72 readers of print outlets among the 1007 respondents who were asked this question.[2] Nevertheless, we find that predicted Magyar Nemzet readers were initially more supportive of the government than both benchmarks, and that this gap remained essentially unchanged after the fallout. We conclude that the political preferences of predicted readers of different outlets did not differentially change around the various events.

A3.2 Advertising by industry and size

In Table A9 we investigate the heterogeneity of advertising in the two main daily newspapers among private advertisers using a specification analogous to (A1) in the Appendix. Column 1 reports a specification which includes one-digit industry indicators and their interaction with right cycle, with

[1] The weights are $w_{ki} = \frac{PS_i(X_k)}{RS_i}$, where $PS_i(X_k)$ is the propensity score that individual k with observables X_k reads media i, and RS_i is the share of people reading media i.

[2] In 2013, 24 percent of subjects read one of the online outlets, but only 7 percent read one of the print outlets at least once a week.

Table A8: Political preferences of predicted readers

Dependent variable:	Predicted readers' support for government (pp)		
	Origo vs Index	Magyar Nemzet vs Népszabadság	Magyar Nemzet vs Index
Origo × new editor	-0.0947		
	(0.254)		
Origo × new owner	-1.03**		
	(0.450)		
Magyar Nemzet × post fallout		-0.848	-2.77
		(5.51)	(5.28)
Origo	-0.358*		
	(0.207)		
Magyar Nemzet		7.09	17.0
		(23.6)	(22.4)
Observations	129,074	90,826	107,324

Note: Each observation is a respondent × outlet pair. Dependent variable measured in percentage points. Observations weighted by propensity score that respondent reads outlet. Bootstrapped standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

"trade" as the omitted industry. It shows that trade and manufacturing firms allocate somewhat less to the right-connected daily than do other industries, but these differences are modest relative to the extent to which state-owned firms tilted their advertising for political reasons. Moreover, we see only small variation with the political cycle in private firms' advertising behavior. Columns 2 and 3 show essentially no heterogeneity by firm size. Column 4-6 report the corresponding weighted results which are qualitatively similar.

A3.3 Inferring the advertising price

An important limitation of our advertising data is that it reports advertising measured at list prices. Potential deviations from list prices do not bias our results as long as connected and unconnected outlets price discriminate in the same way between private and government advertisers. But with advertising favors, differential price discrimination is a possibility: perhaps government advertisers have a different discount at connected outlets than the average discount for all other transactions.

To quantify such targeted price discounts, we follow and extend the approach of Bucsky (2018). We combine hand-collected data from companies' annual reports on their total advertising at real

Table A9: Heterogeneity among private advertisers' allocations in two main dailies

Dependent variable:	Share of right-connected daily, R/(L+R)					
	unweighted			weighted		
Manufacturing × right cycle	-0.0102			0.0213		
	(0.0278)			(0.0443)		
Finance × right cycle	-0.0567			-0.0851**		
	(0.0372)			(0.0401)		
Transportation × right cycle	0.123**			0.0216		
	(0.0578)			(0.0338)		
Real estate × right cycle	-0.0214			-0.0376		
	(0.0440)			(0.0728)		
Other × right cycle	0.0709*			-0.0587		
	(0.0381)			(0.0664)		
Manufacturing	0.0269			0.0503		
	(0.0244)			(0.0503)		
Finance	0.0898***			0.0927**		
	(0.0257)			(0.0390)		
Transportation	0.0694			0.0449		
	(0.0440)			(0.0370)		
Real estate	0.0865**			0.0139		
	(0.0417)			(0.0738)		
Other	0.0451			0.109*		
	(0.0294)			(0.0654)		
Log(employment) × right cycle		0.0111*			0.00874	
		(0.00649)			(0.00578)	
Log(employment)		-0.00299			0.0141**	
		(0.00531)			(0.00661)	
Log(sales) × right cycle			0.00775			0.0138**
			(0.00534)			(0.00633)
Log(sales)			-0.00493			0.00290
			(0.00443)			(0.00878)
Constant	0.0740***	0.127***	0.191**	0.0517**	0.00899	0.0438
	(0.0161)	(0.0320)	(0.0750)	(0.0238)	(0.0416)	(0.155)
Cycle FE	X	X	X	X	X	X
Observations	1578	1520	1545	1578	1520	1545

Note: Each observation is an advertiser × cycle pair. The sample contains the private firm advertisers in our main sample. Columns 4-6 are weighted by the advertiser's total spending in the two newspapers during the sample period. Standard errors clustered by advertiser in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

prices, and their advertising portfolios as measured in our advertising data, to infer two average prices: (i) the price paid by government advertisers to connected media, (ii) the price of all other advertising. We work with the 30 largest private and state-owned advertisers, as measured by their total advertising spending across all media in the Kantar data for the period of 2014-16. We also include advertising on billboards and in television because the annual reports only contain total advertising expenditures.

We assume that the price paid by all advertisers at unconnected outlets, and by government advertisers at connected outlets, is d times the list price. And we assume that the price paid by government advertisers at connected outlets is $\tilde{d}$ times the list price. Then the ratios of advertising spending at real prices relative to list prices equal

$$\frac{\sum_{j\notin G} E_{jt}}{\sum_{j\notin G} W_{jt}} = d$$

$$\frac{\sum_{j\in G} E_{jt}}{\sum_{j\in G} W_{jt}} = \frac{\tilde{d}\sum_{j\in G} a_{jt}^{con} W_{jt} + d\sum_{j\in G}(1-a_{jt}^{con})W_{jt}}{\sum_{j\in G} W_{jt}},$$

where E_{jt} is the advertising expenditure at real prices, W_{jt} at list prices, of advertiser j in year t, and a_{jt}^{con} is the connected advertising share in our advertising data of advertiser j in year t. These equations allow us to solve for the two average prices d and $\tilde{d}$. To implement this approach we need to to measure connected advertising in the television and billboard markets as well. Following MMM (2013, 2015, 2017), in the television market we classify TV2 as connected after its acquisition, and in the billboard market we classify a number of companies owned by the group of Simicska as connected before the fallout.

We find that the unconnected price is 31-34% of the list price depending on the year, while the connected price ranges between 102% and 176%. We believe that paying more than the list price is not likely, and that prices above 100% may be due to advertising included in the annual report which is missing from our advertising data. We interpret the evidence to suggest that private advertisers received substantial discounts while state-owned advertisers paid list prices at connected outlets.

A4 Proofs

Proof of Proposition 1. Maximizing the Cobb-Douglas utility of advertiser j implies

$$\frac{p_1 q_{1j}}{p_2 q_{2j}} = \frac{N_1}{N_2}\exp[\nu_j + G_j\cdot(\theta + \delta(s_1 - s_r))]$$

where we used that $\nu_{1j} - \nu_{2j} = \nu_j$, $\theta_1 - \theta_2 = \theta$, $\delta_1 = \delta$ and $\delta_2 = 0$. Substituting in $N_1/N_2 = \exp[\alpha + \gamma(s_1 - s_2)]$ and taking logs gives the result.

Proof of Proposition 2. Define the function $\Lambda(z) = \exp[z]/(1+\exp[z])$. Let $z_{1j} = \alpha + \gamma(s_1 - s_2) + \theta G_j + \delta G_j(s_1 - s_r) + \nu_j$, then by (7) we can represent the equilibrium action of advertiser j as $a_{1j} = \Lambda(z_{1j})$. Outlet 1 chooses $\tilde{s}_1$ taking into account the equilibrium strategy of advertisers by maximizing

$$\beta\sum_j W_j\cdot E[\Lambda(\alpha + \gamma(\tilde{s}_1 + \zeta + \xi_1 - s_2) + \theta G_j + \delta G_j(\tilde{s}_1 + \zeta + \xi_1 - s_r) + \nu_j)] - \frac{NT}{2}(\tilde{s}_1 - \widehat{s}_1)^2 \quad \text{(A6)}$$

where we used that $p_{1j}q_{1j} = W_j a_{1j}$ and that $s_1 = \tilde{s}_1 + \zeta + \xi_1$. Differentiating with respect to $\tilde{s}_1$ and using the fact that $\Lambda'(z) = \Lambda(z)(1 - \Lambda(z))$ gives the first order condition

$$\beta \sum_j W_j \cdot E[\Lambda(z_{1j})(1 - \Lambda(z_{1j})) \cdot (\gamma + \delta G_j)] = NT(\tilde{s}_1 - \widehat{s}_1)$$

or equivalently

$$\tilde{s}_1 = \widehat{s}_1 + \frac{\beta}{NT} \sum_j W_j \cdot mas_j \cdot (\gamma + \delta G_j) \tag{A7}$$

which gives (8). Equation (9) can be derived analogously. Note that the objective function of each outlet is smooth, bounded from above, and defined for all real $\tilde{s}_i$. Thus in any equilibrium the first-order condition needs to hold for each outlet.

A5 Structural analysis: estimation, credibility, counterfactuals

A5.1 Structural estimation

In the first step of our structural estimation we estimate (7) in OLS, weighting observations by

$$\omega_{jtm} \equiv \frac{W_{jtm}}{\sum_t \sum_j W_{jtm}}$$

where t stands for period and m stands for market. This implies $\sum_j \sum_t \omega_{jtm} = 1$ for each market, so that in specifications that include two markets the markets have equal weight. Then, using the estimated residuals $\hat{\nu}_{jtm}$ we estimate σ_ν^2 using the sample equivalent of M2 as

$$\hat{\sigma}_\nu^2 = \frac{1}{J} \sum_m \sum_t \sum_j W_{jtm} \hat{\nu}_{jtm}^2$$

where J is the number of (advertiser,period) cells.

The second step requires, given a vector of parameters (ω^D, ω^S), numerically solving the model for the equilibrium. Here a key observation is that the difference between relative *measured* slant $s_i - s_r$ and relative *equilibrium* slant $\tilde{s}_i - \tilde{s}_r$ is the measurement error term ξ_{ir}. Indeed, recalling $s_i = \tilde{s}_i + \zeta + \xi_i$ and $s_r = \tilde{s}_r + \zeta + \xi_r$, the unobserved slant component cancels and $s_i - s_r = \tilde{s}_i - \tilde{s}_r + \xi_{ir}$. We can then rewrite the equilibrium-characterizing equations (8) and (9), which express relative measured slant, into equations expressing relative equilibrium slant by removing the ξ error terms:

$$\tilde{s}_1 - \tilde{s}_r = (\widehat{s}_1 - \widehat{s}_r) + \frac{\beta\gamma}{NT} \cdot \sum_j mas_j \cdot W_j + \frac{\beta\delta}{NT} \cdot \sum_{j:G_j=1} mas_j \cdot W_j \tag{A8}$$

and

$$\tilde{s}_2 - \tilde{s}_r = (\widehat{s}_2 - \widehat{s}_r) + \frac{\beta\gamma}{NT} \cdot \sum_j mas_j \cdot W_j. \tag{A9}$$

To solve the model we solve this system of equations for $\tilde{s}_1 - \tilde{s}_r$ and $\tilde{s}_2 - \tilde{s}_r$. This requires first showing that the right-hand sides only depend on $\tilde{s}_i - \tilde{s}_r$ (and the parameters (ω^D, ω^S)), i.e., that the problem is well defined. This follows because, recalling the notation $z_{1j} = \alpha + \gamma(s_1 - s_2) + \theta G_j + \delta G_j(s_1 - s_r) + \nu_j$, we can write $z_{1j} = \alpha + \gamma(\tilde{s}_1 - \tilde{s}_2 + \xi_1 - \xi_2) + \theta G_j + \delta G_j(\tilde{s}_1 - \tilde{s}_r + \xi_{1r}) + \nu_j$ and $a_{1j} = \Lambda(z_{1j})$, which thus only depends on the equilibrium relative slants, parameters and error terms, and therefore $mas_j = E_{\nu,\xi}(a_{1j}(1 - a_{1j}))$, which takes expectations over the error terms, indeed only depends on model parameters and the equilibrium relative slants.

To solve the equations we compute the expectations in mas numerically as

$$\widehat{mas}_j = \frac{1}{K}\sum_{k=1}^{K} a_{1j}(\nu_j^k, \xi_{1r}^k, \xi_{2r}^k)[1 - a_{1j}(\nu_j^k, \xi_{1r}^k, \xi_{2r}^k)],$$

where $K = 200$, and ν_j^k and ξ_{ir}^k are random draws from the distributions $\sqrt{W_j}\nu_j \sim N(0, \hat{\sigma}_\nu^2)$ and $\xi_{ir} \sim N(0, \hat{\sigma}_\xi^2)$. This allows us to numerically compute the right-hand sides of (A8) and (A9) for given values of $\tilde{s}_i - \tilde{s}_r$, and then we use standard numerical methods to solve the system of equations.

We denote the equilibrium relative slants obtained by solving the model, $\tilde{s}_i^* - \tilde{s}_r^*$, as $\Delta\tilde{s}_i^*(\omega^S)$ to emphasize that they depend on the supply parameters ω^S. We then estimate the supply parameters using the simulated minimum distance estimator

$$\hat{Q} = \hat{g}(\omega^S)' I \hat{g}(\omega^S),$$

where I is the $(2E+1) \times (2E+1)$ identity matrix, and $\hat{g}(\omega^S)$ is the $2E+1 \times 1$ vector of the sample equivalents of moments M3 and M4

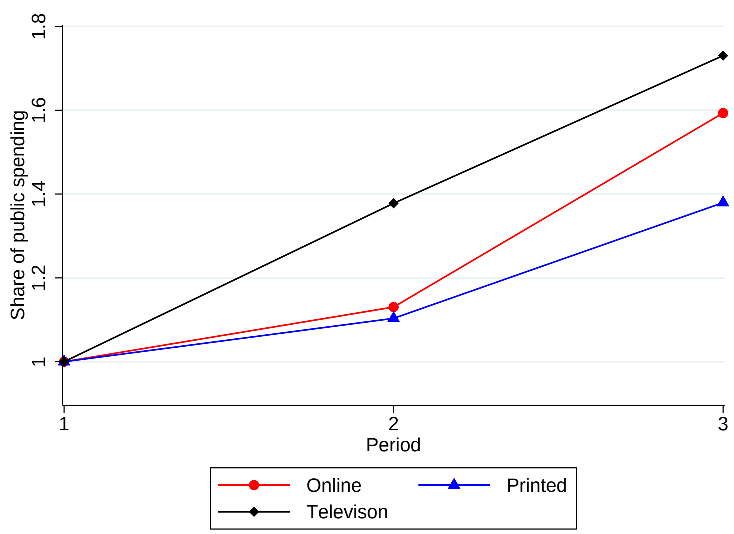
$$\hat{g}(\Omega^S) = \begin{bmatrix} \left[\sum_\tau (\Delta s_{i,e,\tau} - \Delta\tilde{s}_{i,e}^*(\omega^S))\right]_{(i,e)=(1,1)}^{(2,E)} \\ \sum_\tau \sum_e \sum_i (\Delta s_{i,e,\tau} - \Delta\tilde{s}_{i,e}^*(\omega^S))^2 - \sigma_\xi^2 \end{bmatrix}$$

where $\Delta s_{i,e,\tau} = s_{i,e,\tau} - s_{r,e,\tau}$ is the measured relative slant of media i in episode e month τ, and $\Delta\tilde{s}_{i,e}^* = \tilde{s}_{i,e}^* - \tilde{s}_{r,e}^*$ is the "true" relative slant implied by the model for media i in episode e.

As described in the text, if all ideological bliss points are allowed to vary with the period then the number of parameters would be $2E + 2$. Identification thus relies on our assumption that the same owner's ideology is unchanged between periods. For flexibility, we allow the ideological bliss point of reference outlet to be time varying. As a result, the relative ideologies $(\hat{s}_i - \hat{s}_r)$ may vary between periods in a given market; but the relative ideology of media 1 relative to media 2 $(\hat{s}_{1,e} - \hat{s}_{2,e})$ is fixed across two periods if both media had stable ownership.

Our estimation strategy exploits the first-order conditions, but is subject to the concern that at the estimated parameters, the strategy profile that meets these conditions is not an equilibrium. We address this concern by numerically showing that at the estimated parameters, each outlet's strategy is a global maximizer holding fixed the opponent's strategy. Doing this only requires looking at deviations within a bounded interval, because the quadratic loss in (1) ensures that choices of slant outside this interval are dominated by choosing the ideal point.

Figure A1: Public advertising share in different markets



We draw inference by bootstrapping the two-stage procedure. We resample advertisers in the first step and months in the second step. Since we resample advertisers and not (advertisers, period) cells, our estimates are robust to within-advertiser correlation over time in the residuals ν.

A5.2 Credibility and Robustness

Budget trends. To address the identification concern that the aggregate volume of government advertising may have been endogenous to events in the online market, in Figure A1 we plot the government's share in total advertising in the online, print and television markets in the three periods we use for the online structural analysis. Although there are differences between the three markets, online trends do not stand out and there is a general increase in all three, suggesting that the budget increase was not specific to events in the online market.

Alternative reference. To address the concern that the choice of hvg.hu as the reference outlet may affect the results, we re-estimate our structural model with another outlet critical of the government, 444.hu, as the reference. Table A10 reports the results. While the point estimates of β are now higher, the qualitative patterns are similar to those in Table 4.

Adjusting for the advertising price. To adjust for the fact that we only observe list prices, based on the results in Appendix A3.3 we create an augmented advertising dataset in which we adjust all private spending, and state-owned spending at unconnected media outlets, by a factor of 0.33; while we keep list prices for state-owned spending in connected outlets. Because we think that such price favors were unlikely while Telekom was the owner, we only apply the high price for Origo after the change in owner. We then re-estimate our structural model using these augmented data. The results are reported in Table A11 and show that while the point estimates of β are again higher, otherwise the patterns are similar to those in Table 4.

Table A10: Alternative reference outlet

	Online	Print	Pooled	Pooled, flexible ideology in print
Demand parameters				
Govt preference for slant δ	201	320	228	228
	(119, 269)	(146, 457)	(152, 298)	(154, 293)
Reader preference for slant γ	-53	-120	-67	-67
	(-87, -25)	(-259, 45)	(-107, -26)	(-114, -24)
Supply parameters				
Weight on profit β	3.22	3.38	3.13	2.26
	(1.36, 10.34)	(1.03, 10.10)	(1.60, 6.39)	(1.05, 5.73)
Relative ideal point $\widehat{s}_1 - \widehat{s}_2$ (percentage points)				
online, before	-0.4		-0.4	-0.2
	(-1.4, 0.0)		(-1.0, 0.0)	(-0.9, 0.1)
online, after	1.3		1.3	1.4
	(0.3, 1.7)		(0.5, 1.7)	(0.7, 1.8)
print, before		1.0	1.1	1.4
		(0.7, 1.4)	(0.8, 1.4)	(0.5, 1.9)
print, after				1.0
				(0.7, 1.4)

Note: Bootstraped 95% confidence intervals in parentheses.

A5.3 Counterfactuals: Decomposition

In Section 4.6 we compute the model-implied equilibrium slants in different counterfacual scenarios in the online market by numerically solving (A8) and (A9) for $\tilde{s}_1 - \tilde{s}_r$ and $\tilde{s}_2 - \tilde{s}_r$. In doing this, as in the estimation procedure we compute the expected value in mas_{jt} using a Monte-Carlo technique by randomly drawing $K = 200$ realizations of ν and ξ.

We explore four counterfactuals. (1) Benchmark. We set $\delta = 0$ and keep Telekom the owner throughout. (2) Ideology. We keep $\delta = 0$ but let owner ideology change as in the data. (3) Favor exchange. We set δ to its estimated value but keep Telekom the owner throughout. (4) Empirical. Here δ is at its estimated value and ideology changes as in the data. Because we include the realized error terms in the counterfactual calculations, in this scenario the model reproduces the data.

As an example, recalling the notation that $\Delta s_i = s_i - s_r$ is relative measured slant, the model-

Table A11: Alternative advertising prices

	Online	Print	Pooled	Pooled, flexible ideology in print
Demand parameters				
Govt preference for slant δ	541	688	570	570
	(377, 665)	(409, 901)	(429, 682)	(428, 681)
Reader preference for slant γ	-52	-149	-65	-65
	(-86, -22)	(-338, 54)	(-103, -28)	(-103, -29)
Supply parameters				
Weight on profit β	3.50	4.25	3.78	3.12
	(1.44, 11.67)	(0.81, 13.02)	(1.55, 7.44)	(0.84, 8.52)
Relative ideal point $\widehat{s}_1 - \widehat{s}_2$ (percentage points)				
online, before	-0.3		-0.3	-0.2
	(-1.3, 0.1)		(-0.8, 0.0)	(-1.0, 0.2)
online, after	1.4		1.2	1.4
	(0.3, 1.7)		(-0.3, 1.7)	(0.5, 1.8)
print, before		1.0	1.0	1.2
		(0.7, 1.4)	(0.7, 1.4)	(-0.2, 1.8)
print, after				1.0
				(0.7, 1.4)

Note: Bootstraped 95% confidence intervals in parentheses.

implied relative measured slant in the benchmark scenario is

$$\Delta s^{\mathrm{B}}_{i,t} = \Delta\tilde{s}^{*}_{i,t}\left(\delta = 0, (\widehat{s}_{1t} - \widehat{s}_{2t} = \widehat{s}_{\mathrm{Tkom}} - \widehat{s}_{\mathrm{Index}})_{t=1,2,3}\right) + \hat{\xi}_{ir,t}.$$

The first term on the right hand side is the model-implied relative equilibrium slant when $\delta = 0$ and in all three periods the gap in ideal points between the two outlets equals the gap we estimated between Telekom and Index.[3] And the second term is our estimate of the within-period average of the realized measurement error term. Since in the counterfactual we use the estimates from column 1 of Table 4 in which the model is just identified, we perfectly match M3 and hence in practice $\hat{\xi}_{ir,t} = 0$.

[3] Note that this gap, in combination with the estimated difference between the ideal points of Index and the reference in the three periods, pins down all differences between ideal points, which is what is required to solve for equilibrium.

Using the model-implied relative slants Δs_i we compute corruption coverage, denoted CC, for both outlets as

$$\mathrm{CC}_{i,t}^{S} = \mathrm{CC}_{r,t} - \Delta s_{i,t}^{S},$$

where S represents one of our four scenarios, i.e, $S \in \{B, I, F, E\}$. This expression follows from our definition that measured slant is the negative of the share of articles covering corruption scandals, $s_{i,t} \equiv -\mathrm{CC}_{i,t}$.

The ideology and favor exchange effects reported in Table 5 are computed as $(\mathrm{CC}_t^S - \mathrm{CC}_t^B)/\mathrm{CC}_t^B$ where $S = I$ respectively $S = F$, and the substitution effect is computed to ensure that the sum of the ideology, favor exchange and substitution components equals the difference between the empirical and the benchmark scenarios.

We can also compute counterfactual effects for the average reader. Using the equilibrium relative slants and equation (4) we compute reader shares as

$$\frac{N_{i,t}^S}{N} = \frac{\exp[\alpha_i + \gamma \Delta s_{i,t}^S]}{\sum_{l=1}^{2} \exp[\alpha_l + \gamma \Delta s_{l,t}^S]},$$

and then combine these with the corruption coverage of each outlet to compute the average reader's corruption exposure as

$$\overline{\mathrm{CC}}_t^S = \sum_{i=1}^{2} \frac{N_{i,t}^S}{N} \mathrm{CC}_{i,t}^S.$$

A5.4 Counterfactuals: Owner ideology

For the results in Table 6, we compute the expected value of the owner's objective (1)—which we label "net profit" because it nets out the ideology cost—in four counterfactual scenarios that vary the ideology of the owner and the presence of advertising favors. We index the scenarios by $S \in \{old,\ new\} \times \{F,\ NF\}$, where old and new refer to the ideology of the old respectively the new owner, while F and NF to the presence or absence of advertising favors.

The first term in (1) is expected revenue, which is proportional to the expected advertising share

$$E[a_{1j,t}^S] = E_{\xi,\nu} \left\{ \Lambda \left[\alpha + \gamma \cdot (\Delta \tilde{s}_{1,t}^{*S} + \xi_{1r,t} - \Delta \tilde{s}_{2,t}^{*S} - \xi_{2r,t}) + \theta \cdot G_j + \delta \cdot (\Delta \tilde{s}_{1,t}^{*S} + \xi_{1r,t}) \cdot G_j + \nu_{j,t} \right] \right\}.$$

After solving for the counterfactual equilibrium which gives $\Delta \tilde{s}_{i,t}^{*S}$ on the right-hand side, we compute the expectation by randomly drawing 200 realizations of ν and ξ.

The second term in (1) is the ideology cost, which is a function of $\tilde{s} - \hat{s}$. Once we solve for equilibrium, all differences between measured, equilibrium, and ideal slants can be computed. In particular, using the fact that $\tilde{s}_{r,t} = \hat{s}_{r,t}$, we can write

$$\tilde{s}_{i,t} - \hat{s}_{i,t} = (\tilde{s}_{i,t} - \tilde{s}_{r,t}) - (\hat{s}_{i,t} - \hat{s}_{r,t})$$

where the first-term is the equilibrium relative slant we obtain by solving the model, and the second term is the gap between the ideal points of the outlet and the reference which we set as a parameter in the counterfactual.

We then compute the net profit advantage of the new owner as a share of the revenue of the old owner in the absence of favoritism:

$$\text{Net profit advantage}^{Z} = \frac{V^{new,Z} - V^{old,Z}}{R^{old,\ NF}}$$

where V is the net profit (value) and R is the revenue of Origo, and $Z \in \ \{F,\ NF\}$. Columns 1 and 2 of Table 6 report this net profit advantage with and without favoritism.

A5.5 Counterfactuals: Impacts of environment and policy

To obtain the results in Table 7 we evaluate counterfactuals that vary the level of the advertising budget, and the ideology and connection status of Origo's owner. We compute counterfactual corruption coverage and net profits using the steps outlined in A5.3 and A5.4.

In the first set of counterfactuals we vary the advertising budget. Denoting the factual budget profile by W and the counterfactual budget profile by $\tilde{W}$, Table 7 reports

$$\text{Effect on coverage} = \frac{CC^{\tilde{W}} - CC^{W}}{CC^{W}}$$

In the second set of counterfactuals we vary both the advertising budget and Origo's owner. We index the scenarios by $S \in \{W,\ \tilde{W}\} \times \{NF,\ FI\}$ where NF is the counterfactual with Telekom ownership and no favoritism and FI represents the presence of favors and a pro-government shift in ideology. Table 7 reports

$$\text{Effect on return to connected pro-govt owner} = \frac{(V^{\tilde{W},FI} - V^{\tilde{W},NF}) - (V^{W,FI} - V^{W,NF})}{R^{W,NF}}.$$

Finally, in Table 8 we calculate the effect of capturing the independent outlet Index on media content. In order to do so, we evaluate a new counterfactual where both outlets receive advertising favors, so $\delta_1 = \delta_2 = \delta$. Table 8 reports

$$\text{Effect on coverage} = \frac{CC^{BC} - CC^{E}}{CC^{E}},$$

where BC refers to the counterfactual in which both outlets are captured and E to the empirical scenario. And we compute impacts on the average reader along the lines discussed at the end of Appendix A5.3.

A6 Identifying scandals

We used the following algorithm to identify scandals involving the allegation of the abuse of public resources. (1) A team of two research assistants and the two authors went through articles on Index, Origo, hvg,hu and 444.hu in the period of interest and identified potential corruption scandals. We only identified a story as a scandal if the two authors and a research assistant agreed. (2) We developed a set of keywords for each scandal. Our objective was to find a small number of keywords that are directly related to the nature of the scandal, and hence are likely to appear in all articles about that scandal, and unlikely to appear in articles not about that scandal. In some cases, for example for stories involving the spectacular success in procurement auctions and rapid wealth accumulation of a personal friend of the prime minister, the same keywords—the first name and last name of this person—served for multiple scandals. In some cases we combined the keywords with AND or OR operators to more precisely capture the scandals. (3) We identified the articles containing those keywords. Then the two research assistants looked at a random sample of the identified articles. There were a few cases when some of the articles were not about the scandal. In these cases we refined the keywords, and repeated the search. (4) This process concluded with 43 sets of keywords and 13,299 articles covering scandals in the outlets we study. Importantly, while it is possible that we missed or misclassified some scandals, by comparing differences between outlets over time, such classification errors are going to cancel. The list of keywords and the associated relationships required to get a match are provided in Table A12.

Table A12: List of keywords

1.	MNB alapítvány
2.	Pallas Athéné OR PAGEO OR PADS OR PADA OR PADOC OR PADMA OR PADI
3.	L. Simon László AND földárverés
4.	Mészáros Lőrinc
5.	Habony Árpád
6.	Tiborcz István
7.	Rogán AND Portik
8.	Vida Ildikó AND kitiltás
9.	Szijjártó AND (luxusvilla OR 167 millió OR Dunakeszi)
10.	Lázár János AND utazás AND (Svájc OR Olasz)
11.	(trafik OR dohány) AND (mutyi OR koncesszió OR pályázat)
12.	Simicska Lajos AND közgép
13.	Rogán Antal AND V. kerület AND ingatlan
14.	Rogán Antal AND vagyonnyilatkozat AND (lakás OR ingatlan)
15.	századvég AND tanulmány AND tasz
16.	Tasó László AND vagyonnyilatkozat
17.	Hatvanpuszta AND Orbán Viktor
18.	századvég AND 800 millió
19.	állami vezetők hozzátartozói AND közbeszerzés
20.	Szegedi vadaspark AND közbeszerzés
21.	Szőcs Géza AND (Milánói expo OR Milánói világkiállítás)
22.	Farkas Flórián AND Széchenyi-hegy
23.	Farkas Flórián AND Híd a munka világába
24.	Giró-Szász András AND strategopolis
25.	MET AND offshore
26.	letelepedési kötvény
27.	quaestor AND (MNKH OR Kereskedőház)
28.	Lázár János AND luxuslakás
29.	Lázár János AND rolex
30.	Lázár János AND vadászat
31.	(trafik OR koncesszió) AND continental
32.	trafik AND Hadházy Ákos
33.	Orbán Viktor AND fogorvos AND pályázat
34.	kerényi jános AND offshore
35.	Horváth Zsolt AND offshore
36.	századvég AND MNB AND kopint-tárki
37.	Kósa Lajos AND rolling AND stones
38.	állampolgárság AND ukrán AND maffia
39.	debrecen AND városvezetők AND florida
40.	Horváth András AND áfacsalás
41.	Fodor Ibolya
42.	földárverés
43.	Zugló AND Papcsák AND hangfelvétel

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